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DISSOLVED GAS ANALYSIS OF POWER TRANSFORMERS

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ABSTRACT

Transformer insulation aging diagnosis is important for all the condition assessment Dissolved gas analysis (DGA) is one of the most useful techniques and tools to detect the incipient faults in large oil filled transformers. Various methods have been developed to interpret DGA results. Among them are the Key Gas, Rogers Ratio, Logarithmic Nomo graph, Dorenenburg, IEC Ratio and Duval Triangle. This paper uses the DGA data from different cases to test the accuracy and consistency of these methods in interpreting the transformer condition. It also describes the structure and specific features of transformer insulation ageing diagnosis based on artificial neural networks. MATLAB programs using neural network were developed to automate. Also this paper present three fault type, partial discharges (PD), discharges, thermal faults.

KEYWORDS: Transformer, Insulation Aging, DGA, Interpretation Methods, Artificial Neural Network (ANN), Fault Gases

INTRODUCTION

As a major apparatus in a power system, the power transformer is vital to system operation. Techniques for diagnosis and incipient-fault detection are valuable.[2]. A transformer is subject to electrical and thermal stresses which could break down the inculcating materials and release gaseous decomposition products.[4]. Overheating, corona and arcing are three primary causes of fault related gases. Principally, the fault related gases commonly used are hydrogen (H2), carbon monoxide (CO), carbon dioxide (CO,), methane (CH4), acetylene (C2H2), ethane (C2H6), and ethylene (C2H4).[7]. The analysis of dissolved gases is a powerful tool to diagnose developing faults in power transformers. Many diagnostic criteria have been used for the interpretation of the dissolved gases. These methods would find the relationship between the gases and the fault conditions, some of which are obvious and others may not be apparent (hidden relationships).[3]. However, much of the diagnostics relies on experts to interpret the results correctly.[8]. New computer-aided. techniques can consistently diagnose incipient-fault conditions for the novice and in some cases may provide further insight to the expert. Expert system and fuzzy-set approach have been developed to reveal some of the hidden relationships in transformer fault diagnosis.[13]. Expert system derives the decision rules from the previous experience while the fuzzy-set represents the decision rules by using vague quantities.[11]. Artificial neural network method (ANN) has also been used for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by ANN through training process.[5]. A two-step ANN approach is presented in this paper.[14]. The accuracy of the ANN is carefully verified. With two ANNs, high diagnosis accuracy

DISSOLVED GASES -IN-OIL

Analysis Dissolved gases-in-oil analysis (DGA) is a common practice in transformer fault diagnosis. Electrical insulation such as mineral oils and cellulosic materials degrade under excessive thermal and electrical stresses, forming by

product gases which can serve as indicators of the type of stress and its severity. Dissolved gas-in-oil concentrations, relative proportion of gases, and gas generation rates (gassing rates) are used to estimate the condition of a transformer. Commonly used gases include hydrogen (H2), methane (CH4), acetylene (C2H2) ethylene (C2H4), ethane (C2H6), carbon monoxide (CO), and carbon dioxide (CO2). These gases are extracted from the oil under high vacuum and analyzed by Gas Chromatograph to get each gas concentration separately. By interpretation of gas contents, the developing faults in the power transformers can be diagnosed. Many diagnostic techniques have been developed for the interpretation of these gases. This technique includes the conventional key gas method, ratio methods, and recently, the artificial intelligent methods. The key gas method relates key gases to fault types and attempts to detect four fault types (overheating of oil, overheating of cellulose, partial discharge, and arcing) based on key gas. contents (C2H4, CO, H2, C2H2). The ratio methods are coding systems that assigns certain combination of codes to a specific fault type.The Codes are generated by calculating gas ratios and comparing the ratios to predefined ratio intervals. A fault condition is detected when a code combination fits the code pattern of the fault. Because the number of possible code combination is larger than the number of fault types, “no decision” often results from the ratios Methods such **as** Doemenburg Ratios, Rogers Ratios and IEC Ratios.

All of these methods are able to detect thermal decomposition, partial discharge, and arcing faults. In an actual diagnosis process, other information such as the variability of dissolved-gas data and the influence of loading and environmental factors on these data is usually also taken into consideration. Recently, application of artificial intelligence (AI) has shown very promising results in DGA. These techniques include expert system, fuzzy logic, evolutionary algorithm, and artificial neural network (ANN). The Artificial Neural Network method can be used more accurately for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by ANN through training process.

DGA FAULT ANALYSIS TECHNIQUES

Roger’s Ratio Method

This method uses the 4-digit ratio code generated from the 5 fault gases (H2, CH4, C2H6, C2H4, and C2H2) to determine 15 diagnosis rules for transformer conditions.

IEC Basic Ratio Method

This method originated from the Roger’s Ratio method, except that the ratio C2H6/CH4 was dropped since it only indicated a limited temperature range of decomposition the faults are divided into nine different types.

Duval Triangle Method

This method has proven to be accurate and dependable over many years and is now gaining in popularity.

Key Gas Analysis Method

Key-Gas analysis method could present damage levels of the power transformer and its cause by analyzing the levels of combustible gases. The method defines the level of damage by considering all of the total combustible gases, which can be classified in different ranges.

Method of Fault Analysis Classification

The fault interpretation results from each method are used in the main interface to determine the fault analysis classification by using a single fault analysis to find the common result.

DIAGNOSIS OF FAULT TYPE

Transformer fault diagnosis is used widely by the public and very high accuracy of diagnosis of neural network methods result of neural network input and output can express the relationship between variablesThe greatest advantage is that does not require complicated mathematical calculations, as long as the use of pre-defined sample data entry to training can be used as fault types of transformer diagnosis. This article uses the most widely used back-propagation neural network. Back-propagation neural network is to apply the basic principles of the Gradient Steepest Descent Method theory Its operation process is divided into two stages, The first stage is the learning phase By learning algorithm would repeatedly enter the correct sample and constantly adjust the weights of the network nodes, so that the network output value and target value approximation. The second stage is the recall phase: Network at this stage to accept outside input, and in accordance with the computing algorithm, after the results sent by the output layer. The output would be high-temperature overheating, the overheating temperature, low temperature overheat, arc discharge and partial discharge of five types of failure. Therefore, to adopt three layers network architecture: input layer has seven neurons, output layer has three neurons, hidden layer has six neurons, and its structure as shown in Figure [7].

Table 1: Neural Network Efficiency for Known Input Vectors Using IEC Criterion

1	H2	CH4	C2H2	C2H4	C2H6	CO	CO2	Class
2	120	31	94	66	130.8	48	271	3
3	260	215	277	334	35	130	416	3
4	530	345	250	266	85	3900	20000	3
5	960	4000	6	1560	1290	15800	50300	1
6	110	62	250	140	90	680	6470	3
7	1860	4980	1600	10700	6895.824	158	1300	1
8	90	28	32	31	8	1380	11700	3
9	100	200	11	670	110	100	650	1
10	1570	735	1740	1330	87	711	4240	3
11	1100	1600	26	2010	221	641.9375	1430	1
12	92600	10200	6.5	8.1666667	533.875	6400	103151	2
13	1	27	1	4	49	53	254	1
14	3700	1690	3270	2810	128	22	86	3
15	57	24	30	27	2	540	2518	3
16	24700	61000	1560	42100	26300	14400	30400	1
17	1500	395	323	395	28	365	576	3
18	2800	2800	3600	3500	234	92	718	3
19	26788	18342	6.5	27	2111	704	15053.43	2
20	1900	285	7730	957	31	681	732	3

Note: class(1) main thermal faults, class(2) main partial discharges fault, class(3) main discharges fault

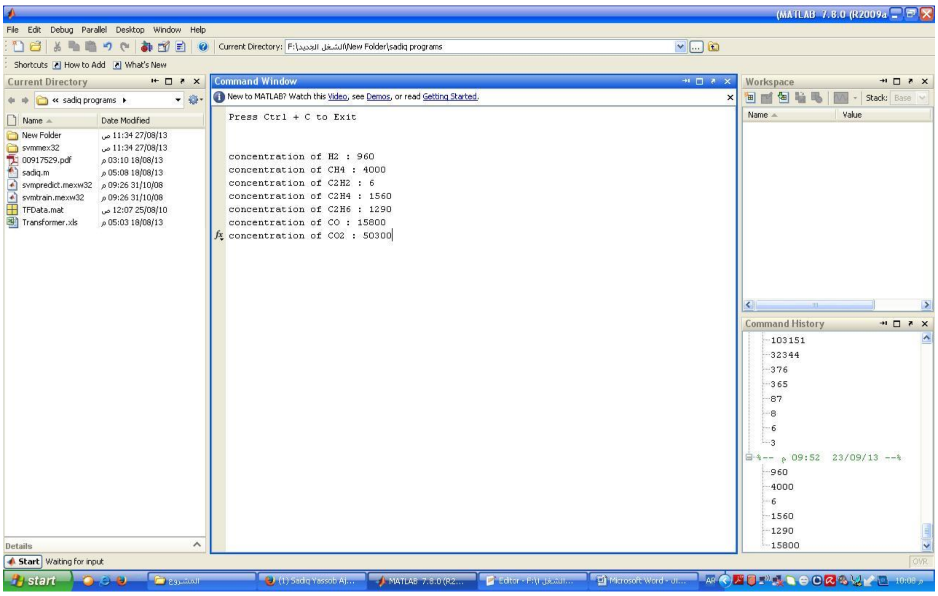

Figure 1: Input Data of Gas in PPM

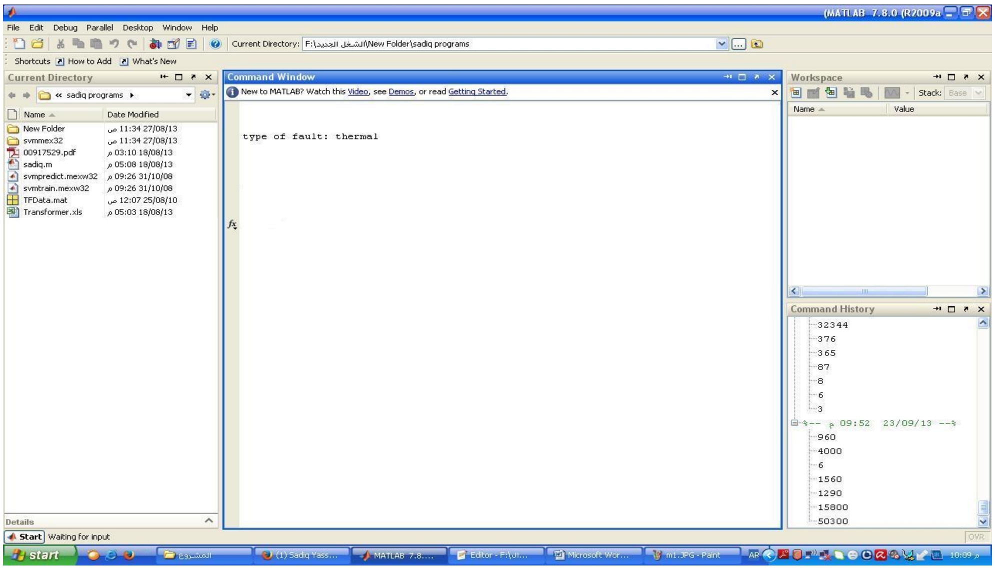

Figure 2: Result Thermal Fault

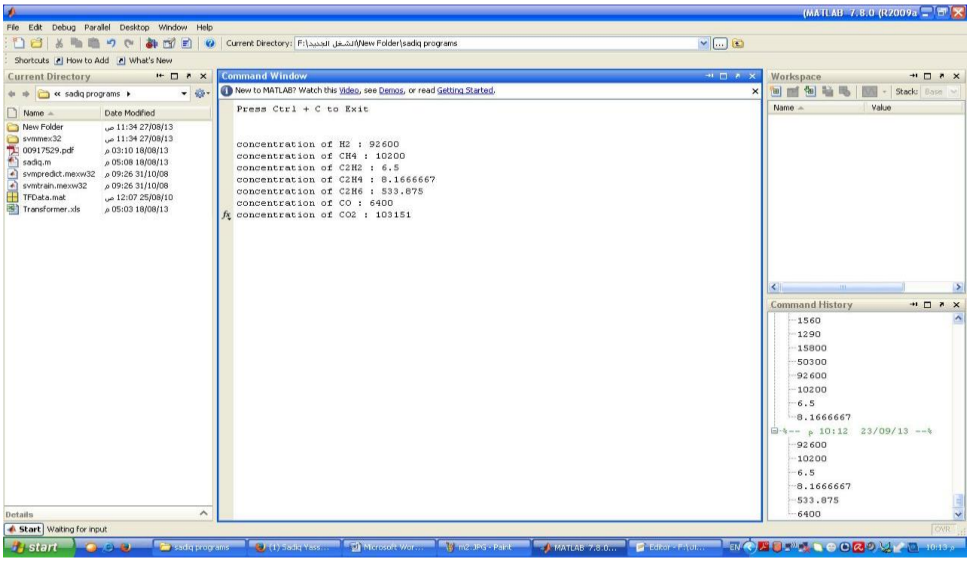

Figure 3: Input Data of Gas in PPM

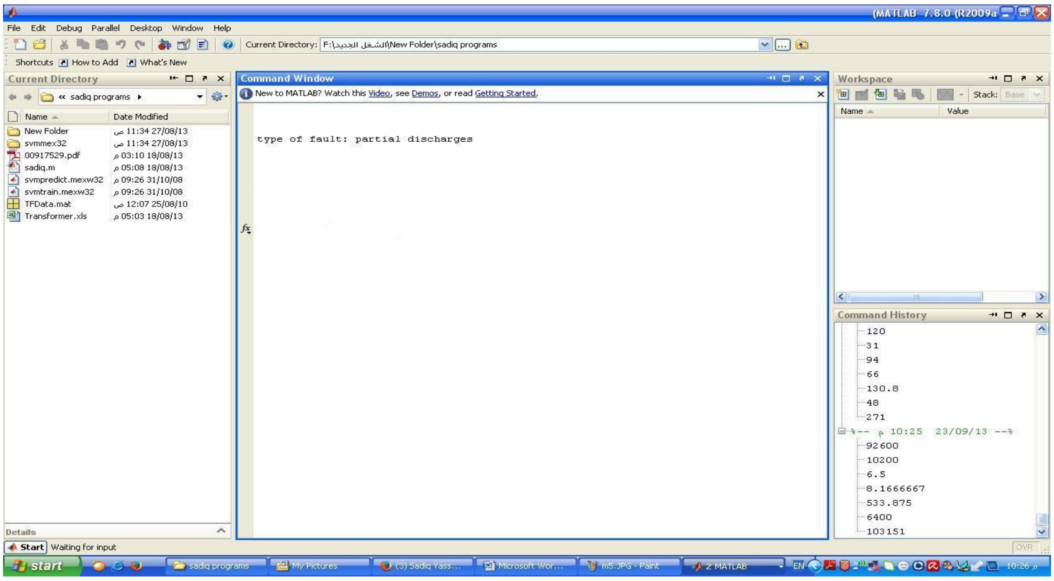

Figure 4: Result Partial Discharges Fault

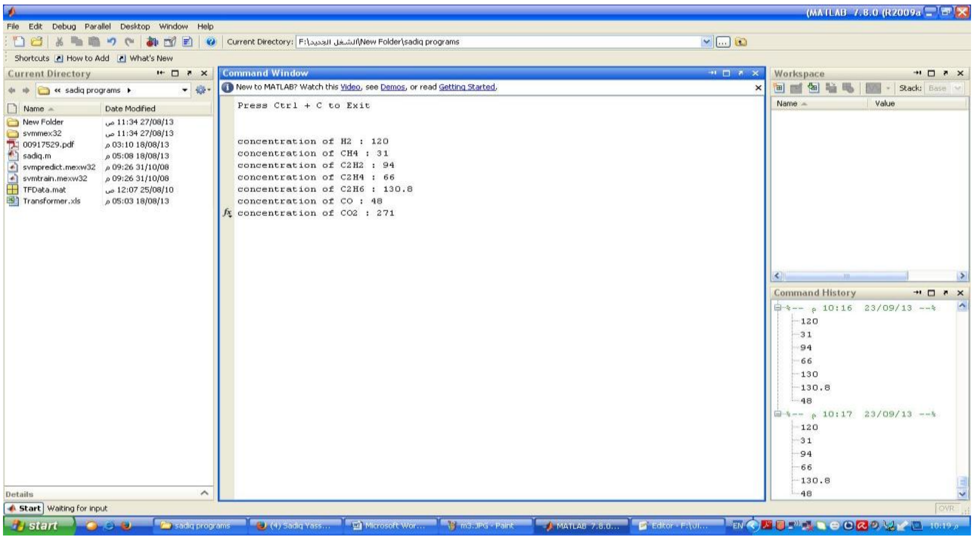

Figure 5: Input Data of Gas in PPM

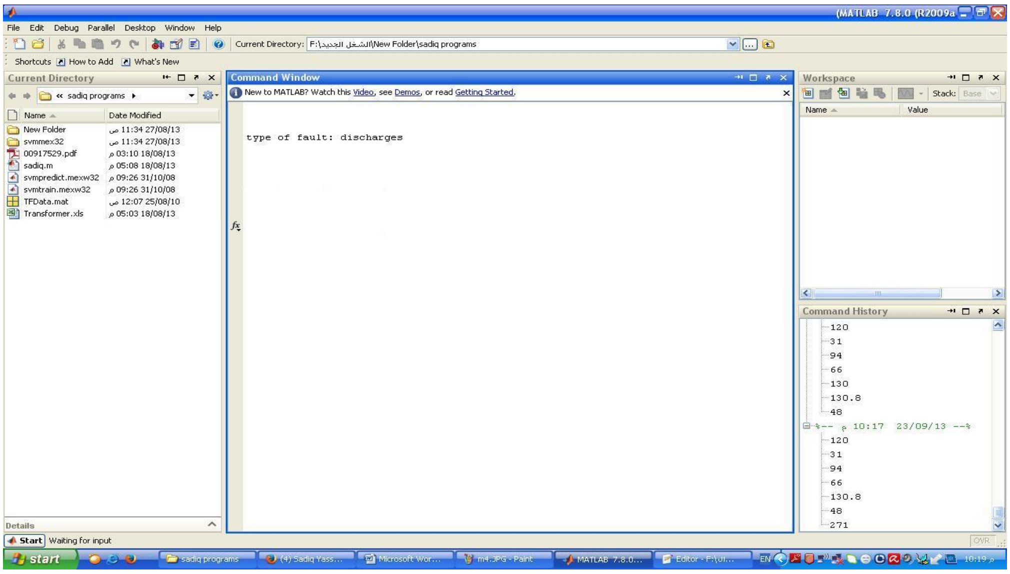

Figure 6: Result Discharges Fault

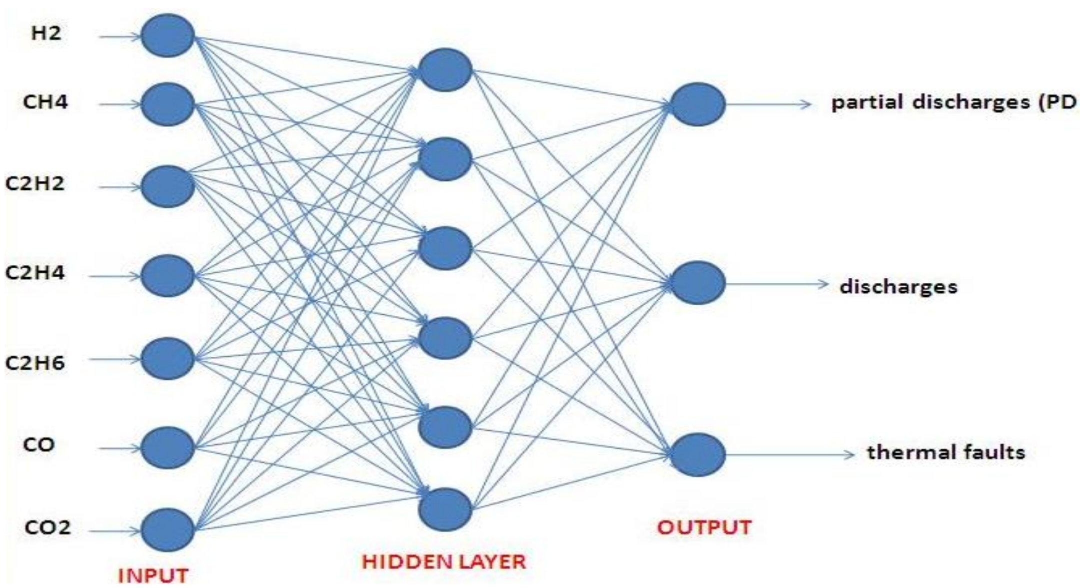

Figure 7: Structure of Neural Network

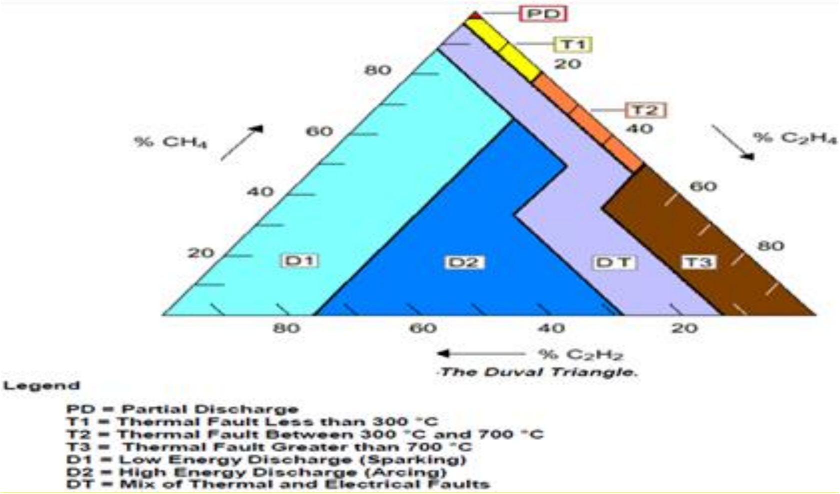

Figure 8: Duval Triangle

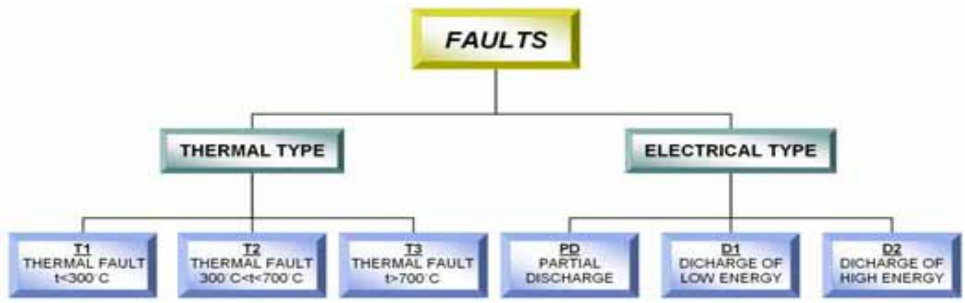

Figure 9: Faults Type

Table 2: Permissible Limits of Dissolved Gases in a Healthy Transformer

Gas	Less than 4 years in service	4-10 years in service	More than 10 years in service
Hydrogen (H_2)	100/150 ppm	200/300 ppm	200/300 ppm
Methane (CH_4)	50/70 ppm	100/150 ppm	200/300 ppm
Acetylene(C_2H_2)	20/30 ppm	30/50 ppm	100/150 ppm
Ethylene (C_2H_4)	100/150 ppm	150/200 ppm	200/400 ppm
Ethane (C_2H_6)	30/50 ppm	100/150 ppm	800/1000 ppm
Carbon Monoxide (CO)	200/300 ppm	400/500 ppm	600/700 ppm
Carbon-di-oxide (CO_2)	3000/3500 ppm	4000/5000 ppm	9000/12000 ppm

Table 3: Gas Analysis and Corresponding Faults

Gases	Possible faults	Findings
All the gases and Acetylene present in large amounts.	High energy electrical arcing 700° C and above.	Same as above with metal discoloration. Arcing may have caused a thermal fault.
H_2, CO, CH_4, C_2H_6 and C_2H_4	Thermal fault between 300° C and 700° C.	Paper insulation destroyed. Oil heavily carbonized.
H_2, CO	Thermal faults less than 300° C in an area close to paper insulation (Paper is being heated).	Discoloration of paper insulation. Overloading or cooling problem. Bad connections. Stray current path and/or stray magnetic flux.

Table 4: Gas Analysis and Corresponding Faults

H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2 present in large amounts. If C_2H_2 is being generated, it indicates continuance of arcing CO will be present if paper is being heated.	High energy discharges (arcing)	Metal fusion, (poor contacts in tap changer or lead connections). Weakened insulation, from ageing and electrical stress. Carbonised oil. Paper overhauling/ destruction if it is in the arc path.
H_2, CH_4 (CO if discharges involve paper insulation). Possible trace of C_2H_6	Low energy discharges (sparking)	Pinhole puncture in paper insulation with carbon and carbon tracking. Possible carbon particles in oil. Loose grounding of metal objects.
H_2 possible traces of CH_4 and C_2H_6 possible CO.	Partial discharge (Corona)	Weakened insulation from ageing and electrical stress.

NEURAL NETWORK

Neural network uses a large number of simple artificial neurons to imitate the living being neural network uses the artificial neuron to make simple simulation for the biological neuron Through association form and information transmission between the neuron, various kinds of human know feeling, memory, pondering over ability, and even the states of the emotion and mood operation can be in the brain or surface network component includes neuron (Neuron), the unit (Units). The processing information that consists of the node (Nodes) and the minimizing error function dealing with the unit to concentrate and organize in groups, is called layer (Layer). There are three treatment layers for the BPN: input layer, hidden layer, export layer. Each of networks has one input layer. There is one or a lot of hidden layers, which join each other adjacent one while dealing with the nodes of layer to transmit to the next one and one exported layer scientist applies neural network to computer software development setting-up of one kind of neural networks in the theory and development of the way, the back-propagation network (BPN) is most adopted, and belongs to the supervising type of the network

ARCHITECTURE METHODOLOGY

Proposed monitoring and fault diagnosis system mainly consists of type of personal computer, online oil, gas detectors and associated interfaces, software, etc... Through a modem connection with the remote PC can be remotely download and monitoring and diagnosis of fault type part of the program is to combine real-time data. Reference to the benchmarks of Company, Electric Association for Research and ANSI/IEEE, first make a preliminary monitoring, and then use back-propagation neural network for fault type diagnosis.

ADVANTAGES AND LIMITATIONS

The advantages of using computer- based software for DGA analysis on oil filled insulation transformer are It utilizes four methods to predict faults in transformer insulation oil in the same time It reduces the time to calculate and analyze oil-filled transformer faults by using DGA system It gives better and more accurate results to confirm the transformer incipient fault It reduces the human-error on interpreting the fault on DGA system.

CONCLUSIONS

Several combination methods, machine learning and rules mining techniques were introduced in electrical and computer systems To implement these methods in fault diagnostic systems, new fusion approaches were proposed for the

conventional DGA techniques and related features. DGA techniques with several ratios and criteria have long been used for power transformer fault diagnosis. They have relative advantages and disadvantages. Many artificial techniques were applied to obtain a more accurate result. Nevertheless, there are limited investigations that have used DGA knowledge and the learning ability of artificial intelligent systems simultaneously. In this investigation, two combination systems were applied in the decision level and feature level for conventional DGA techniques. Gas concentrations of 196 faulty cases were collected for training and validating the methods. Three types of faults including partial discharge, thermal faults and discharge fault were selected as the main faults. The results showed:

- Combination in the feature level, using the flexible neuro-fuzzy system, gives the most reliable results. It also determines the weight of each ratio for individual fault detection networks.
- Combination in the decision level gives more reliable performance than individual techniques and is less accurate than feature level fusion. More parameters for adjusting in the learning process and the basic limitation of each DGA technique are the possible reasons.
- Both combination approaches showed dominant performances compared to conventional DGA techniques, while Duval's technique had the best performance in the studied DGA techniques.

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Dr. Jyoti Shrivastava has done her graduation in electrical engineering and her post graduation in design of heavy electrical equipment at present she is serving as an Senior Assistant Professor in Electrical Engineering Department at college of engineering and technology SHIATS Allahabad India She has several international and national paper to her credit Her filed of interest and research are power system control and operation and condition monitoring of heavy electrical equipment her research aims to increase T&D system capacity and enhancing system reliability.